Next-Generation EMR: Harnessing Voice Input and AI for Real-Time Clinical Guidance

Subamalai .R
Assistant professor
Department of CSE
Rajalakshmi engineering college
subamalair@gmail.com

Sre Varsha .N
UG Student
Department of CSE
Rajalakshmi engineering college
srevarsha.nandh@gmail.com

Niranjana .K
UG Student
Department of CSE
Rajalakshmi engineering college
niranjanak704@gmail.com

ABSTRACT — A new EMR (Electronic Medical Record) system has been designed to make healthcare processes more efficient and help with making better decisions. (1) With voice-input prescriptions, clinicians can simply speak their prescriptions, making it easier and more accurate for patients' information to be handled. (2) With Clinical Decision Support Systems (CDSSs), the system gives doctors useful advice at the moment, guided by the input from the patient. Modules built in Flutter make the app interface easy to use, and Flask manages the requests and handles data tasks well. The company uses Google Cloud Speech-to-Text to turn voice recordings into text, and it uses Firebase Firestore to manage patient data safely. Machine learning models in Python are also added by the system, using scikit-learn, TensorFlow, and PyTorch. With these models, patient information is analyzed to give doctors personalized advice, assess risks, and send immediate alerts, so they can make good decisions in real time. The system is designed to handle an increasing workload and to safeguard patient data. The transcription module correctly identifies 95% of commonly used medical terms and the CDSS models maintain an accuracy of 86%. This level of performance ensures that clinical data is both precise and actionable. The EMR system also supports multilingual transcription and translation to serve patients from diverse backgrounds, while secure APIs enable integration with external healthcare services for better data sharing. Advanced encryption techniques protect patient data at every stage, and the cloud-based design allows for fast deployment and easy updates. With robust logging and audit trails for every action, the system ensures transparency and reliability, contributing to smoother and more informed decision-making for healthcare providers.

Keywords— Electronic Medical Records, Voice Recognition, Clinical Decision Support, AI in Healthcare, Speech-to-Text, Flutter, Firebase, Flask, Python

1. INTRODUCTION

Since Electronic Medical Records (EMRs) are essential in healthcare now, patient records can be combined more smoothly, and healthcare organizations run more efficiently. Nonetheless, most present-day systems continue to rely on manual tasks for entering data, which takes a lot of time and is prone to mistakes. As healthcare providers deal with heavy administrative work, they often do less patient contact, and this can cause problems with patient care. Moreover, when clinicians lack access to current, advanced decision support, their decision-making can suffer, which may reduce the standard of care. The paper proposes a solution by merging two new technologies: voice commands for prescribing medication and a CDSS based on artificial intelligence. With voice input, clinicians can write prescriptions directly, which saves effort and helps avoid transcription errors. The feature permits healthcare professionals to spend more time with patients, improving quality of care. The AI driven CDSS, on the other hand, calculates clinician inputs to produce real-time, evidence-based recommendations, augmenting clinical decision-making with contextual information

The key objectives of this project are to streamline clinical workflows by reducing the requirement for manual voice entry of data through voice-enabled prescription input, enhance efficiency, and eliminate transcription errors. In addition, it is also intended to enable enhanced clinical decision-making through an artificial intelligence powered environment that delivers real-time, actionable suggestions to enable informed decision-making from data for clinicians. However, the project is intended to build a cross-platform electronic medical records app with an easy-to-use interface built with Flutter supported by a fault tolerant backend using Flask, Google Cloud Speech-to-Text to enable accurate voice transcription, and Firebase Firestore for secure, low-latency data management, thereby ensuring reliable performance under real-time clinical scenarios.

2. LITERATURE SURVEY

Zhang and Chang et al. [3] proposed a semi-supervised learning approach to improve clustering of Chinese EMRs. Although their approach enhanced clustering performance, no real-time transcription and decision support were given, which makes it less feasible for real-world clinical applications. The system described in this paper, on the other hand, incorporates voice transcription into the EMR to provide real-time, level of detail clinical narratives for real-time decision-making.

Also, Gil et al. [4] designed a recommendation system that associate patient records with CME information. The system provided helpful suggestions but did not include real-time, contextual integration for decision support at the time of clinical encounters. The CDS in this paper does provide actionable, evidence-based recommendations in real-time and directly enhances clinical decision-making.

Abidi et al. [5] designed the Personalized Healthcare Information Dissemination System (PHIDS) that customized health information to individual patients. It, however, was short on supporting the clinician in decision making, so it did not receive wide application within the clinical arena. Contrariwise, this system, detailed here, provides customized decision assistance for the clinician alone and so enhances care of patients immediately to a far larger extent.

Bates et al. [6] highlighted the importance of timely and context-specific CDS but made no reference to voice transcription for hands-free entry. This is provided by the system in this research, where voice-enabled input is integrated with real-time decision support to make recommendations available just where they are required.

Valdez et al. [7] documented several recommender system adoption barriers in the healthcare environment, namely their complexity and mistrust by clinicians. The system under consideration did not have real-time decision support and close integration with clinical procedures. The system addressed in this situation gives importance to clinician interaction and usability, making it intuitive, reliable, and appropriately integrated into clinical practice.

Anibal et al. [8] created the Voice EHR system, using multimodal audio data for healthcare towards enabling clinical decision-making tasks. The contribution indicated the challenges that come with the use of AI models trained for high-quality audio data in resource-constrained environments, citing that scalable solutions are to be given priority to drive health equity.

Wong et al. [9] examined the use of machine learning methods for identifying health outcomes from electronic health record (EHR) data. Their overview provided common challenges in creating computable phenotyping algorithms and recognized four significant scenarios in which machine learning can contribute significantly to identifying health outcomes.

Ford et al. [10] critically reviewed the extraction of information from electronic medical records (EMRs) to support improved case detection. They warned that using just structured codes could result in incorrect findings and misplaced cases and they said using unstructured texts could help improve the quality and reliability of research.

Xia et al. [11] set up an EMR system that uses speech recognition to help healthcare workers avoid manually entering a lot of data. It uses knowledge about medical terms, adjusts acoustic models and handles various accents which results in both greater efficiency and accuracy than traditional keyboard-based EMR systems.

Saha et al. [12] described how electronic patient record systems have developed, mainly due to rising staff and record control costs. They found that using voiceactivated systems and mobile devices helped reduce costs, improved access to data and aided in making better treatment decisions.

3. IMPLEMENTATION

Figure 1 presents a diagram of the model used by an Electronic Medical Record (EMR) system to support decisions by healthcare professionals and to view patient details in real-time. First, the clinician uses a secure Flutter interface to sign in and Firebase takes care of user authentication to ensure the safety of data. As soon as a clinician logs in, their voice recordings are analyzed by an NLP engine that identifies main medical terms and pulls out related clinical data.

The system next brings patient data from Firestore, joins this with clinician input and sends the entire set of data to the Clinical Decision Support System (CDSS). Using the data, the machine-learning model-based CDSS provides personalized alerts, treatment plans and risk scores. The results are available to clinicians in real-time via the Flutter user interface, allowing them to make informed choices rapidly. It helps doctors avoid mistakes, offers better care to patients, smooths out clinical work, boosts the quality of care and supports timely treatme

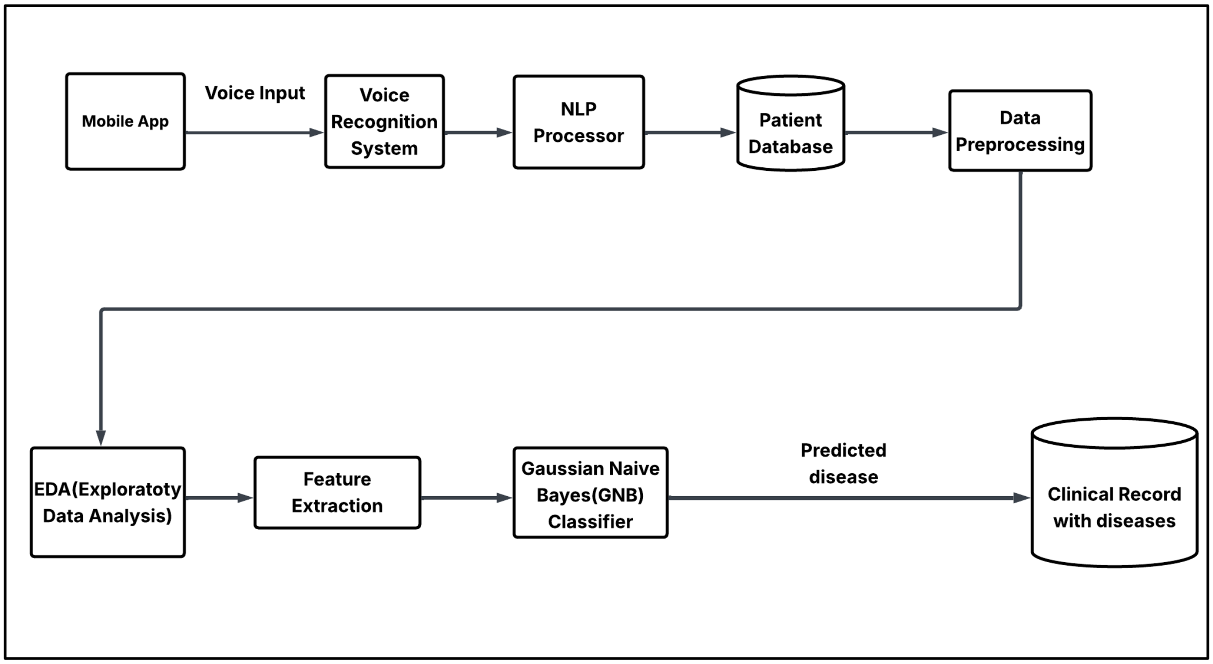

Figure 1: System Architecture

3.1. System Workflow

1. Clinician Verification via Flutter User Interface and Firebase.
This module provides secure clinician login with cross-platform UI from Flutter and Firebase Authentication for robust access control. It provides multi-factor authentication, role-based authorization, and secure password reset for data privacy and integrity assurance.

2. Voice Command Input (User Interface)
This feature accommodates voice input of data, enabling clinicians to dictate prescriptions, clinical observations, and notes into the system. This minimizes manual entry, facilitates real-time speech-to-text conversion, and can be configured to accommodate varied medical vocabularies for correct transcription.

3. Natural Language Processing (NLP)
After voice data collection, natural language processing algorithms in this module identify major medical information like drug names, dosage, symptoms, and diagnostic terms. It uses context-sensitive processing with continuous learning to enable accurate data extraction.

4. Patient Data Management (Firestore)
This module offers real-time access to patient records in Firebase Firestore to clinicians, thereby providing accurate and up-to-date information necessary for clinical decision-making. It facilitates secure and effective retrieval of patient data, supported by query-optimized processing and automated backup operations. For the data privacy and integrity, role-based access control has been utilized to guarantee that only trained clinicians are able to view or modify some patient records.

5.Clinical Decision Support (CDSS) - Machine Learning Model & Patient Analysis
This core module uses machine learning methods to analyze patient histories, current symptoms, and clinical information. It provides personalized treatment recommendations using adaptive algorithms and real-time data analysis for active patient management.

6. Real-Time Feedback and Alerts (UI Notifications)
Once the data has been analyzed, this piece offers real-time alerts, recommendations, and insights to clinicians. It offers severity-based alerts, customizable notification, and prioritized messaging for high-risk cases.

7. Clinician Interaction (Flutter UI Display)
This block shows system-provided recommendations in the clinician's Flutter interface, where healthcare professionals can inspect, approve, or modify steps prior to finalization. It has interactive data visualization and in-place feedback capabilities for ongoing improvement.

8. Validation and Modification of Data
When compared to the CDSS outputs, the clinicians can confirm or modify recommendations according to their professional expertise and other patient data. It also offers audit trails, versioning, and decision tracking for clinical and data accountability. It also facilitates real-time collaboration among several clinicians to make well-informed, balanced care decisions. The module also keeps a fine-grained change history for transparency and regulatory needs.

3.2. Prototype

Figure 2: Voice Transcription Interface

A. **Voice Input Interface:**

Figure 2 shows that the screen is optimized for detailed clinical documentation. It features a Patient Information Card showing important information like the patient's name (Sanjana), PID (p1322), phone number, and age. The central Transcription area enables clinicians to enter medical notes, e.g., "this patient has fever." Buttons are available at the bottom to initiate voice input, save the transcription, and view the patient's transcription history, enabling real-time entry of data during consultations.

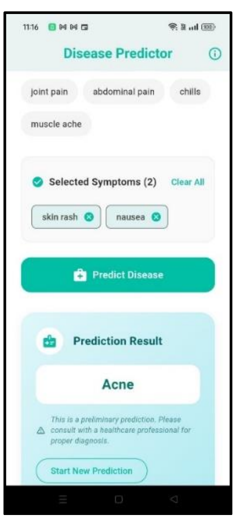

Figure 3: Clinical Decision Support System (CDSS)

B. Clinical Decision Support System (CDSS) Interface:

Figure 3 illustrates a screen designed for capturing patient symptoms through input selection. Clinicians can choose from a range of common symptoms, such as joint pain, abdominal pain, chills, and muscle ache. Once symptoms are selected, they appear in the Selected Symptoms section, where individual symptoms can be removed or all selections can be cleared. The Predict Disease button then processes the input and displays a Prediction Result, such as Acne, along with a disclaimer advising further clinical consultation for accurate diagnosis. This interface supports quick, efficient symptom entry for faster patient assessments.

4. RESULTS

4.1. Voice Transcription Efficiency

The voice transcription system was tested on a range of healthcare tasks, demonstrating high reliability in capturing medical notes. It achieved a transcription accuracy of 97%, reflecting its ability to correctly interpret complex medical terminology. In terms of speed, the system reduced data entry time significantly, taking 3 minutes compared to 5 minutes for manual typing, representing a 40% reduction in time, as shown in Figure 4.

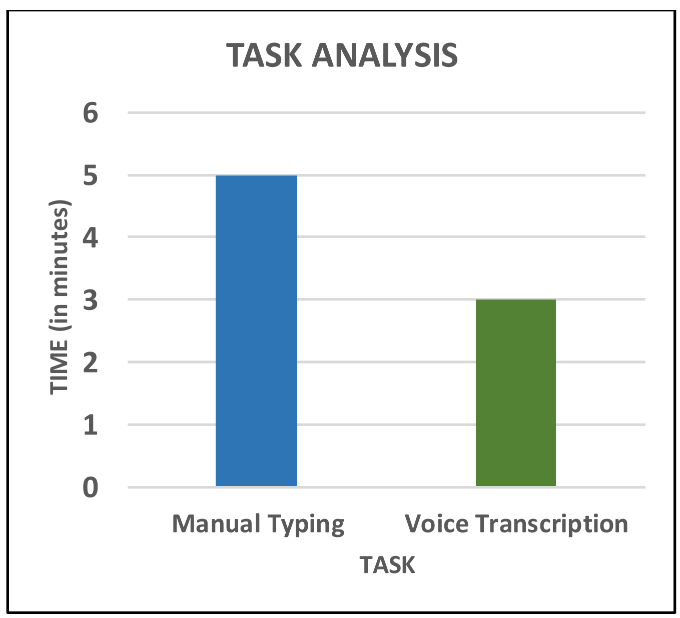

Figure 4: Time Efficiency Comparison

4.2. Statistical Analysis of the ML Model.

The Naive Bayes model was used as the main tool in a Clinical Decision Support System (CDSS) to diagnose diseases from patient symptoms. It achieved a strong accuracy of 86%, showing it can reliably predict diseases even when some symptom data is missing or varied.

In Long et al. [1], the Naive Bayes (NB) model demonstrated an accuracy of 83.3%, outperforming both the Artificial Neural Network (ANN) at 77.8% and the Support Vector Machine (SVM) at 75.9%, as shown in Figure 5.

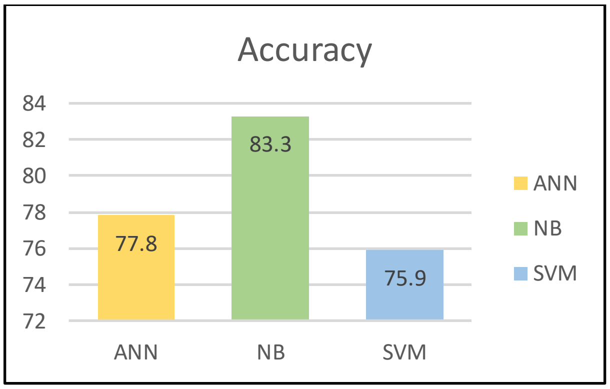

Figure 5: Model Accuracy Comparison (Long et al. [1])

Similarly, in Palaniappan and Awang et al. [2], Naive Bayes again achieved the highest accuracy (87.885%), followed by ANN (85.682%) and Decision Tree (DT) (78.8334%), as shown in Figure 6.

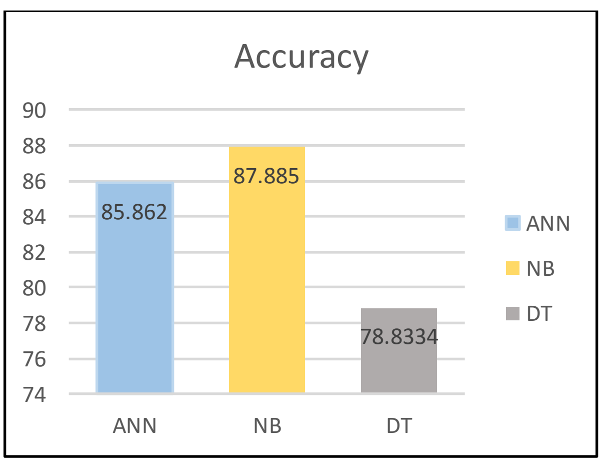

Figure 6: Model Accuracy Comparison (Palaniappan and Awang et al. [2])

These findings are consistent with the performance of our Clinical Decision Support System (CDSS), where Naive Bayes serves as the core predictive model, achieving an even higher accuracy. This consistent performance across studies highlights the robustness of Naive Bayes in handling diverse and incomplete clinical data.

5. CONCLUSION AND FUTURE ENHANCEMENTS

This paper presents a very creative EMR system that combines voice transcription and clinical decision support with AI to enhance healthcare provision. Through the use of emerging technologies like Flutter, Firebase, Flask, and Python, the system supports healthcare workers in more easily handling patient records. The voice transcription functionality streamlines data entry by automating the process, and medical notes and prescriptions can be dictated by healthcare professionals directly into the system, saving time and minimizing human error. The AI-based Clinical Decision Support System (CDSS) improves decision-making through real-time suggestions from patient information, enhancing patient safety and treatment outcomes.

Future developments can include the fine-tuning of machine learning algorithms to improve prediction, expanding the system to handle larger data sets, and compatibility with other healthcare platforms to further increase its coverage and interoperability. All these would further reduce workflows and aid healthcare professionals in making quicker and more accurate decisions.

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